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Lovegrove

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(54) **EDGE COMPUTING DEVICE FOR CONTROLLING ELECTROMECHANICAL SYSTEM OR ELECTRONIC DEVICE WITH LOCAL AND REMOTE TASK DISTRIBUTION CONTROL**

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(22) Filed: **Sep. 2, 2022**

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(63) Continuation-in-part of application No. 17/077,976, filed on Oct. 22, 2020, now Pat. No. 11,438,404.

(51) **Int. Cl.**

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G05B 19/042	(2006.01)
H04L 67/125	(2022.01)
G06N 20/00	(2019.01)
H04L 67/12	(2022.01)
G06N 3/045	(2023.01)

(52) **U.S. Cl.**
CPC ***G05B 19/041*** (2013.01); ***G05B 19/042*** (2013.01); ***G06N 20/00*** (2019.01); ***H04L 67/12*** (2013.01); ***H04L 67/125*** (2013.01); *G06N 3/045* (2023.01)

(58) **Field of Classification Search**
CPC H04L 67/025; G06N 3/045; G05B 19/041; G05B 19/042
See application file for complete search history.

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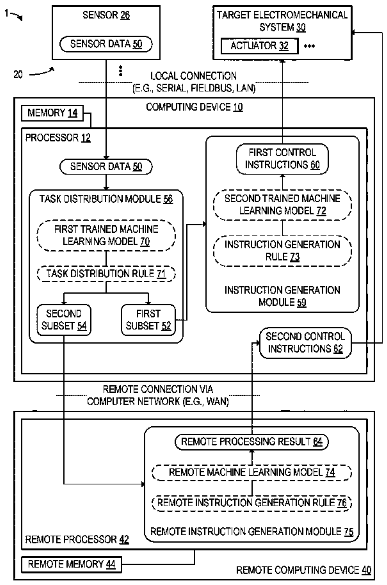
(57) **ABSTRACT**

A computing device, including a processor configured to receive sensor data from a control device. The control device may include a control processor configured to execute control instructions to control an actuator of a target electromechanical system and may further include one or more sensors. The processor may identify a first subset of the sensor data and a second subset of the sensor data. The processor may generate first control instructions based on the first subset and transmit the first control instructions to the control processor of the control device. The processor may transmit the second subset to a remote computing device. In response to transmitting the second subset to the remote computing device, the processor may receive a remote processing result from the remote computing device. The processor may generate second control instructions from the remote processing result and transmit the second control instructions to the control processor.

23 Claims, 12 Drawing Sheets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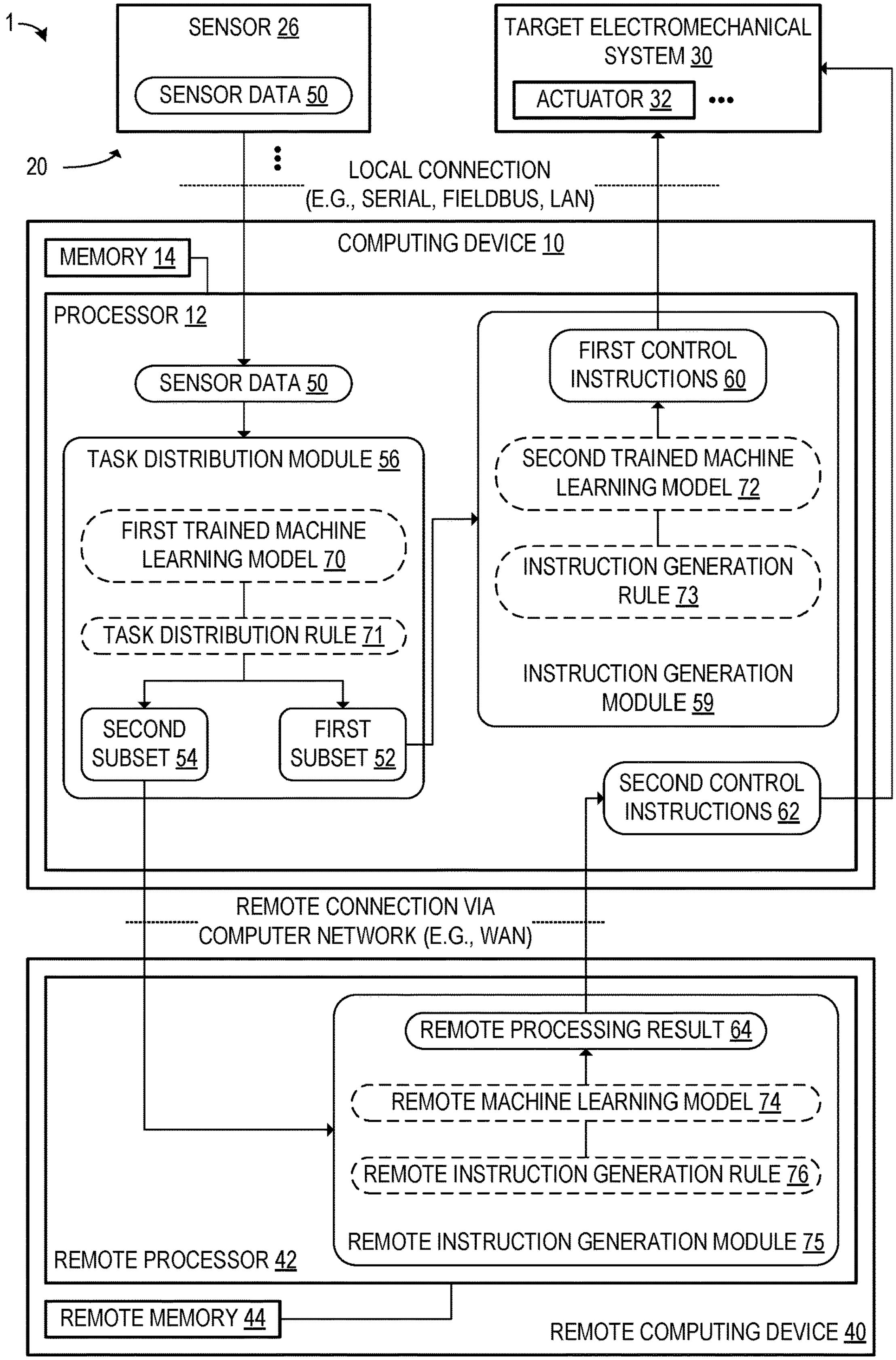
SENSOR DATA 50
TARGET ELECTROMECHANICAL SYSTEM 30
ACTUATOR 32
20
LOCAL CONNECTION (E.G., SERIAL, FIELDBUS, LAN)
COMPUTING DEVICE 10
MEMORY 14
PROCESSOR 12
SENSOR DATA 50
TASK DISTRIBUTION MODULE 56
FIRST TRAINED MACHINE LEARNING MODEL 70
TASK DISTRIBUTION RULE 71
SECOND SUBSET 54
FIRST SUBSET 52
FIRST CONTROL INSTRUCTIONS 60
SECOND TRAINED MACHINE LEARNING MODEL 72
INSTRUCTION GENERATION RULE 73
INSTRUCTION GENERATION MODULE 59
SECOND CONTROL INSTRUCTIONS 62
REMOTE CONNECTION VIA COMPUTER NETWORK (E.G., WAN)
REMOTE PROCESSING RESULT 64
REMOTE MACHINE LEARNING MODEL 74
REMOTE INSTRUCTION GENERATION RULE 76
REMOTE INSTRUCTION GENERATION MODULE 75
REMOTE PROCESSOR 42
REMOTE MEMORY 44
REMOTE COMPUTING DEVICE 40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SENSOR 26
SENSOR DATA 50
TARGET ELECTROMECHANICAL SYSTEM 30
ACTUATOR 32
•••
20
LOCAL CONNECTION (E.G., SERIAL, FIELDBUS, LAN)
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PROCESSOR 12
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FIRST TRAINED MACHINE LEARNING MODEL 70
TASK DISTRIBUTION RULE 71
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FIRST SUBSET 52
FIRST CONTROL INSTRUCTIONS 60
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INSTRUCTION GENERATION RULE 73
INSTRUCTION GENERATION MODULE 59
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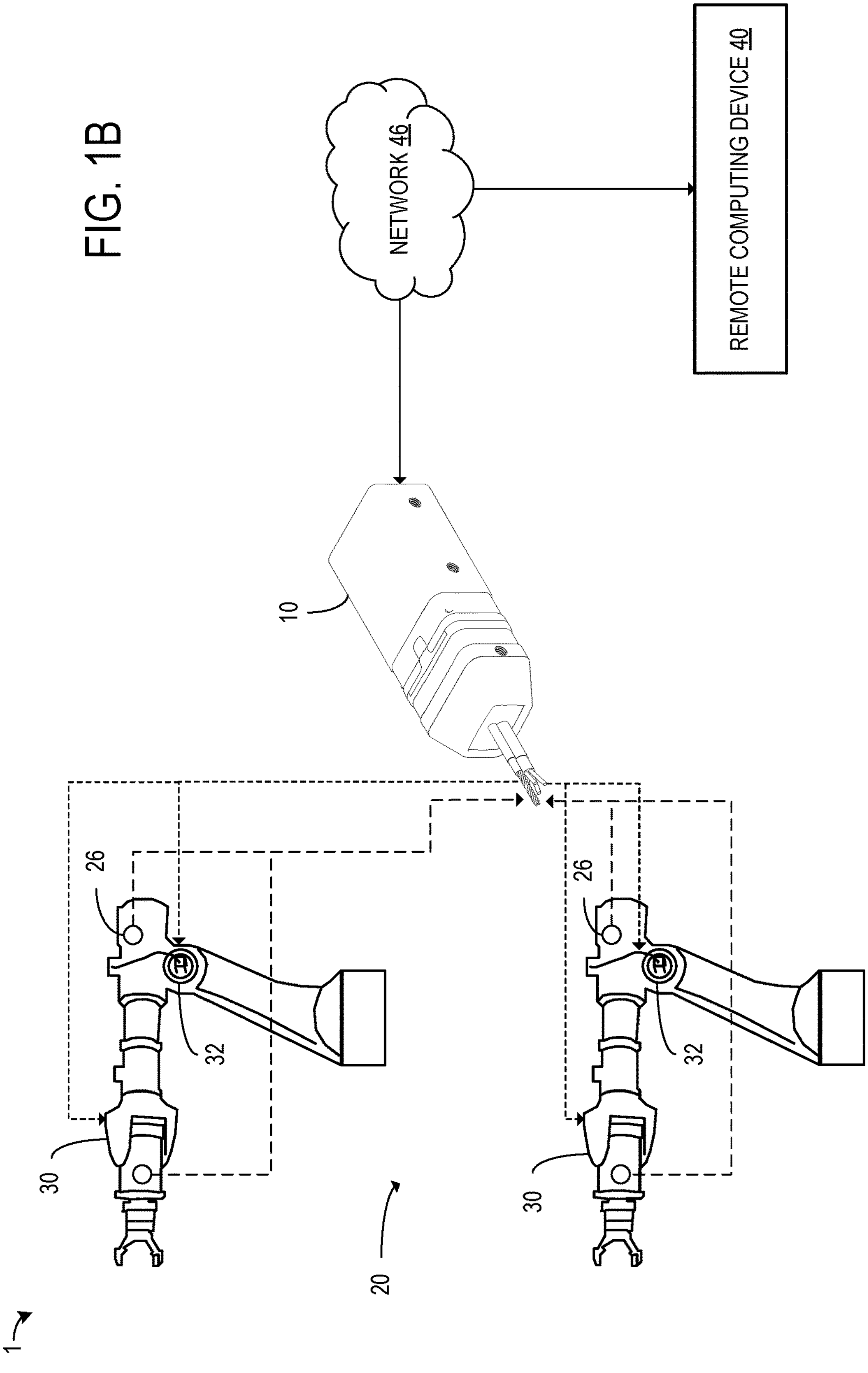
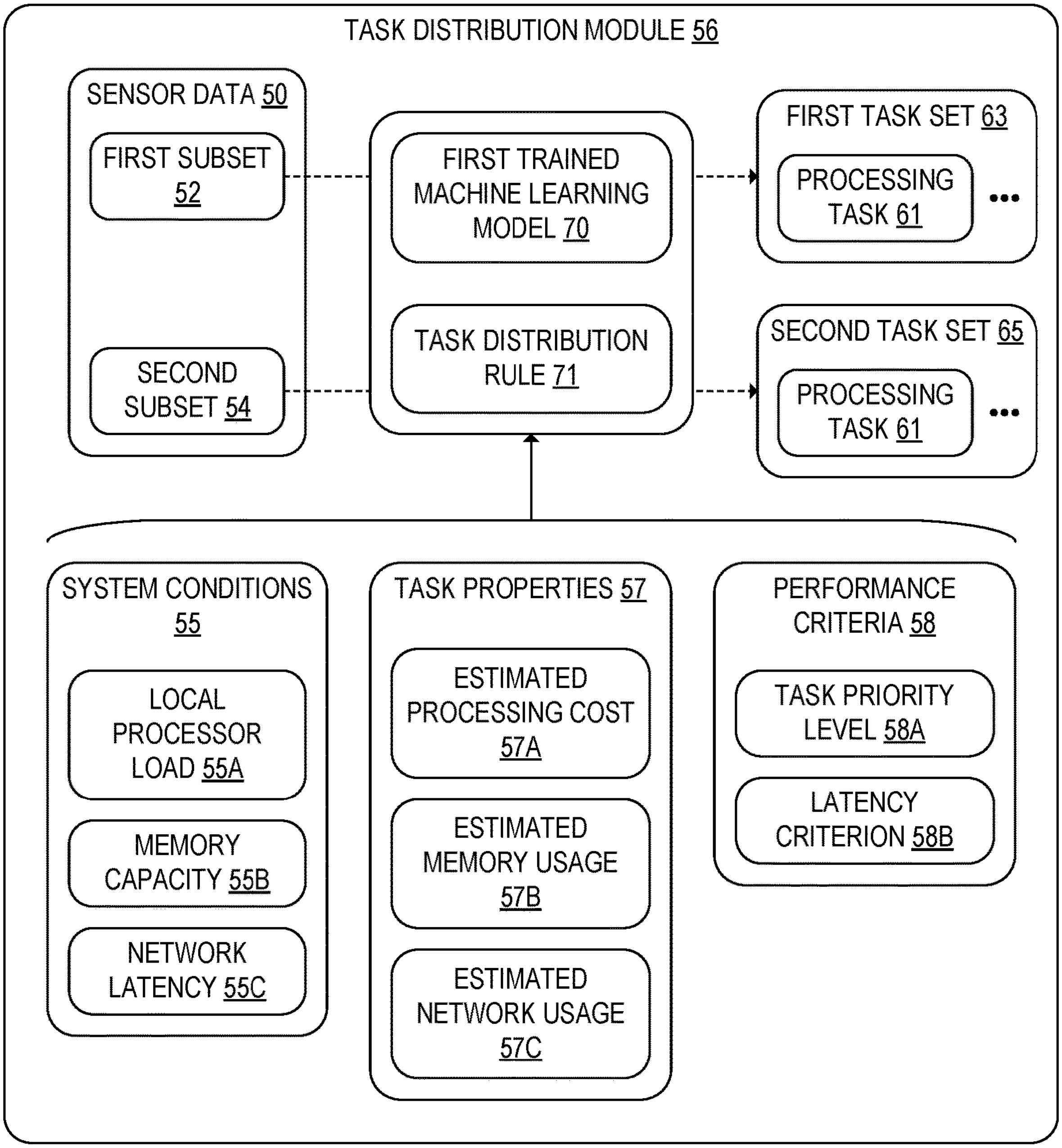
REMOTE PROCESSING RESULT 64
REMOTE MACHINE LEARNING MODEL 74
REMOTE INSTRUCTION GENERATION RULE 76
REMOTE INSTRUCTION GENERATION MODULE 75
REMOTE PROCESSOR 42
REMOTE MEMORY 44
REMOTE COMPUTING DEVICE 40

FIG. 1A

FIG. 1B

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TASK DISTRIBUTION RULE 71
FIRST TASK SET 63
PROCESSING TASK 61
...
SECOND TASK SET 65
PROCESSING TASK 61
...
SYSTEM CONDITIONS 55
LOCAL PROCESSOR LOAD 55A
MEMORY CAPACITY 55B
NETWORK LATENCY 55C
TASK PROPERTIES 57
ESTIMATED PROCESSING COST 57A
ESTIMATED MEMORY USAGE 57B
ESTIMATED NETWORK USAGE 57C
PERFORMANCE CRITERIA 58
TASK PRIORITY LEVEL 58A
LATENCY CRITERION 58B

FIG. 2

FIG. 3

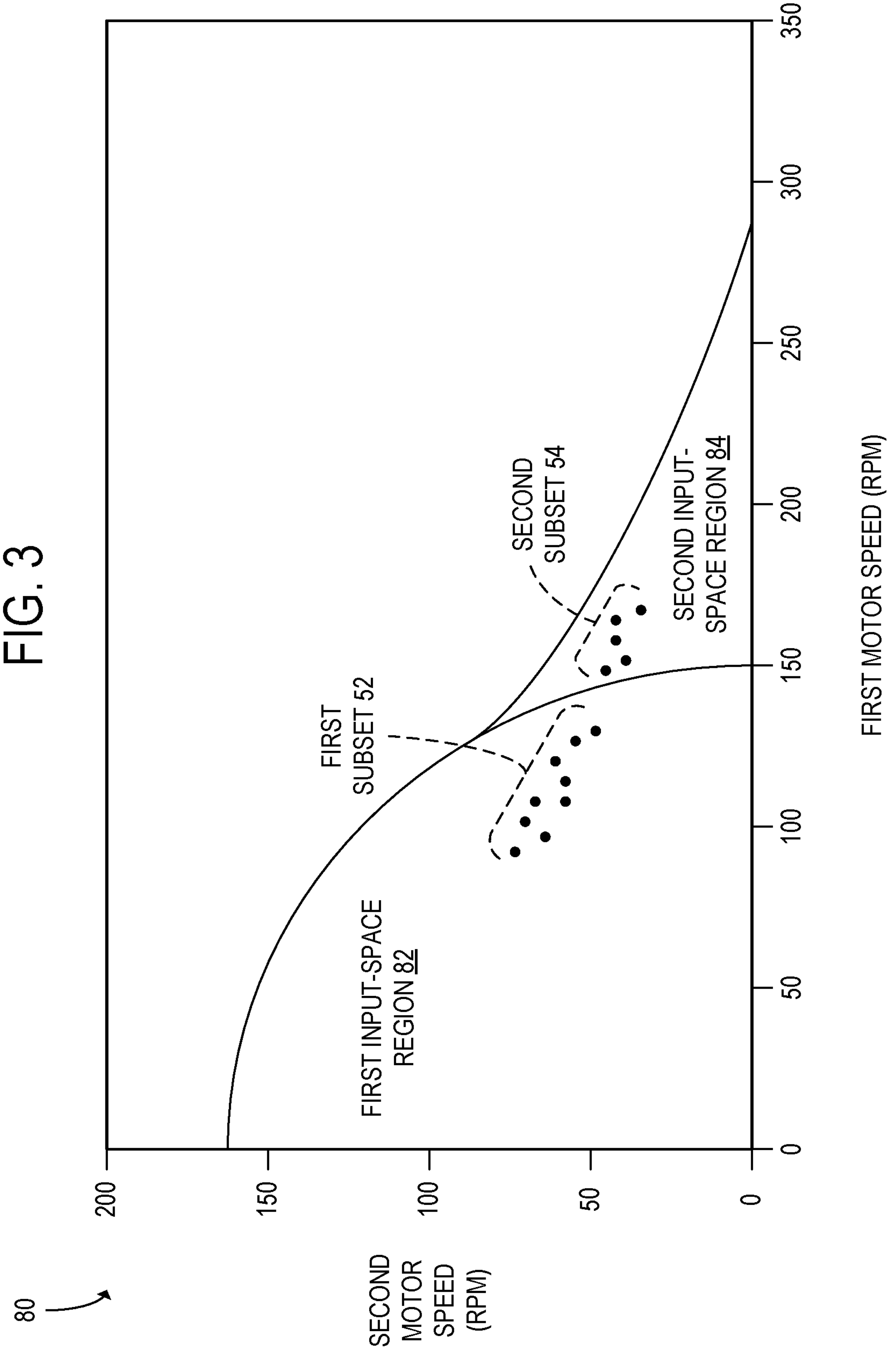
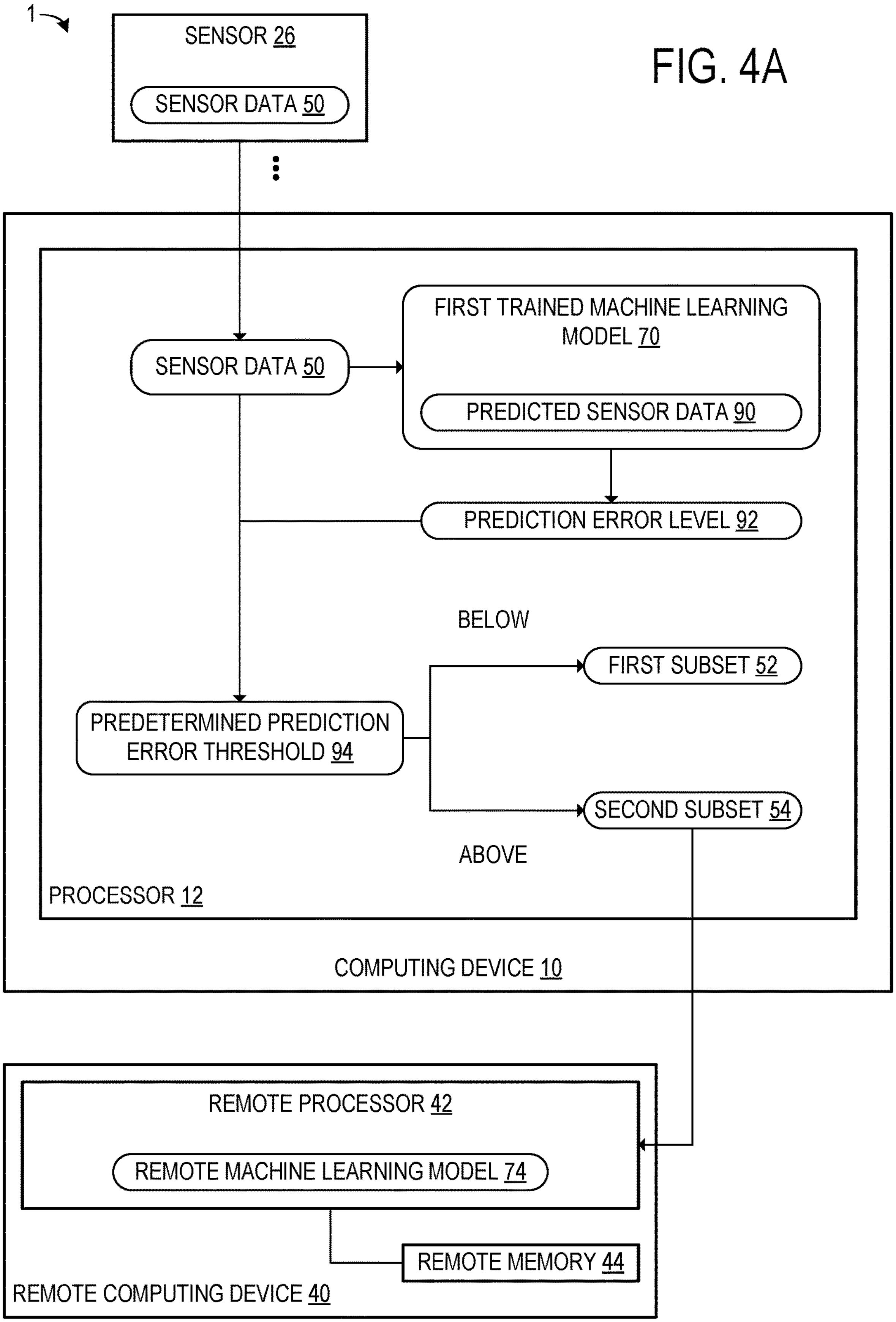

80
SECOND MOTOR SPEED (RPM)
200
150
100
50
0
FIRST MOTOR SPEED (RPM)
0
50
100
150
200
250
300
350
FIRST INPUT-SPACE REGION 82
FIRST SUBSET 52
SECOND SUBSET 54
SECOND INPUT-SPACE REGION 84

FIG. 4A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SENSOR 26
SENSOR DATA 50
SENSOR DATA 50
FIRST TRAINED MACHINE LEARNING MODEL 70
PREDICTED SENSOR DATA 90
PREDICTION ERROR LEVEL 92
BELOW
FIRST SUBSET 52
PREDETERMINED PREDICTION ERROR THRESHOLD 94
SECOND SUBSET 54
ABOVE
PROCESSOR 12
COMPUTING DEVICE 10
REMOTE PROCESSOR 42
REMOTE MACHINE LEARNING MODEL 74
REMOTE MEMORY 44
REMOTE COMPUTING DEVICE 40

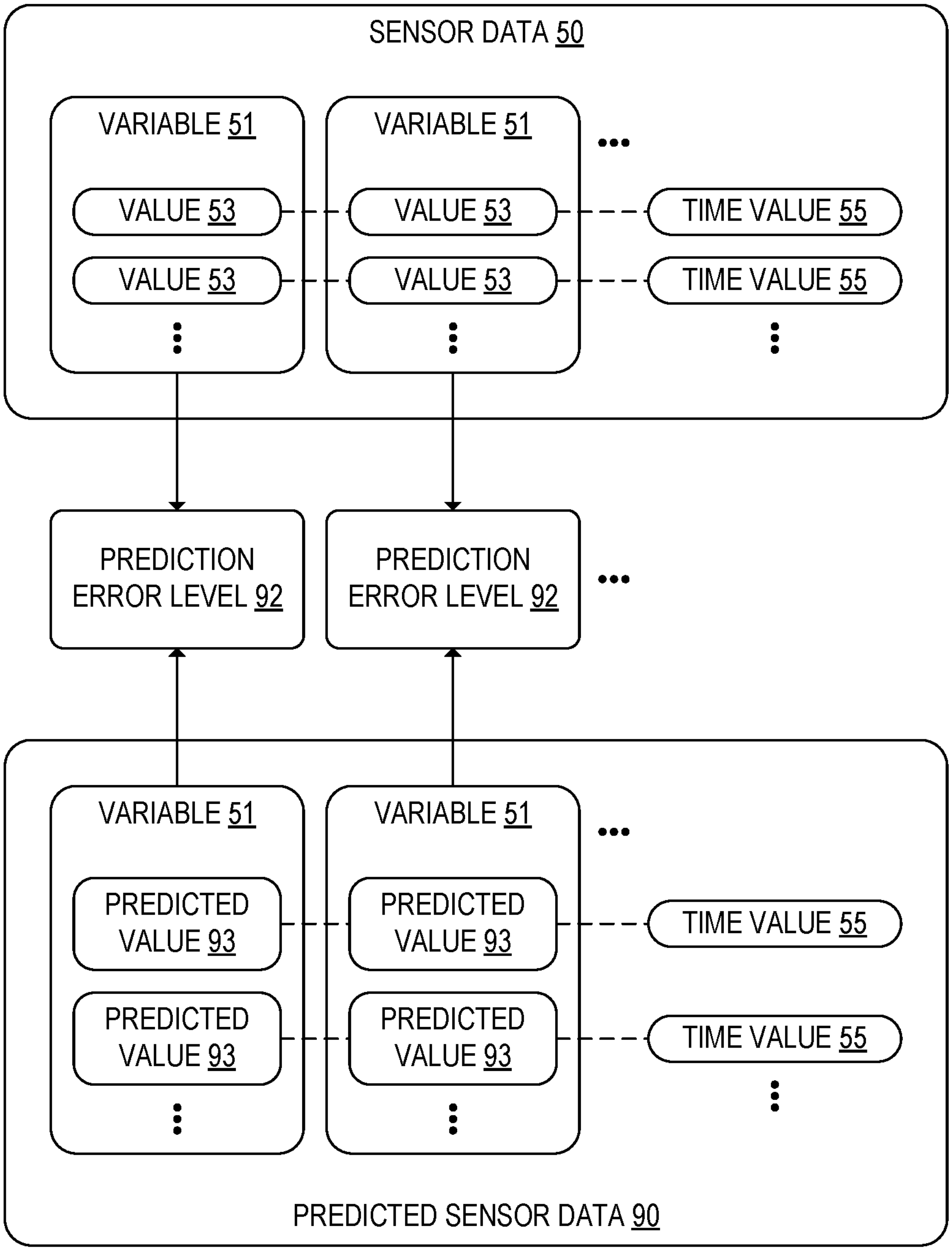
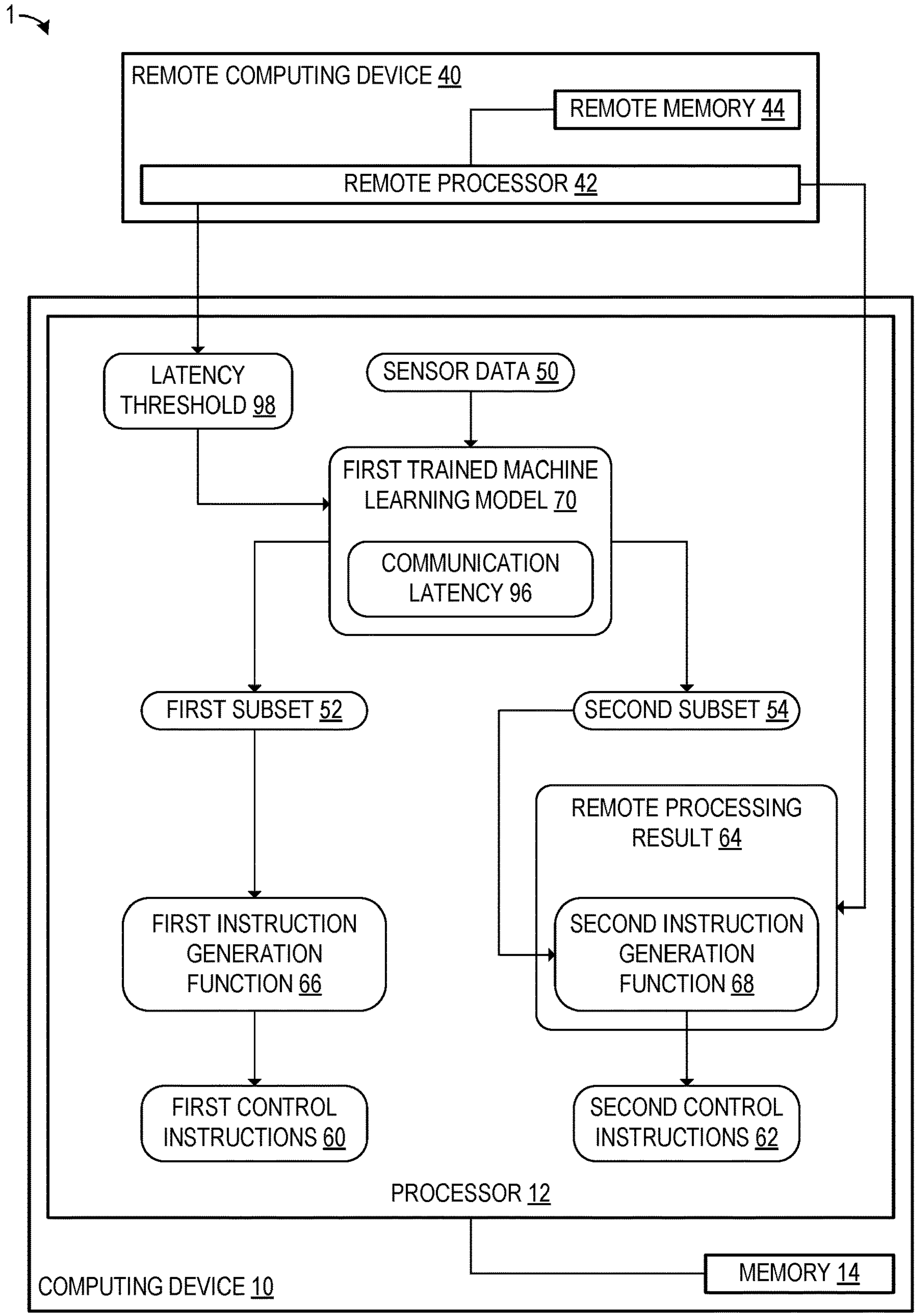

SENSOR DATA 50
VARIABLE 51
VARIABLE 51
VALUE 53
VALUE 53
TIME VALUE 55
VALUE 53
VALUE 53
TIME VALUE 55
PREDICTION ERROR LEVEL 92
PREDICTION ERROR LEVEL 92
VARIABLE 51
VARIABLE 51
PREDICTED VALUE 93
PREDICTED VALUE 93
TIME VALUE 55
PREDICTED VALUE 93
PREDICTED VALUE 93
TIME VALUE 55
PREDICTED SENSOR DATA 90

FIG. 4B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REMOTE MEMORY 44
REMOTE PROCESSOR 42
LATENCY THRESHOLD 98
SENSOR DATA 50
FIRST TRAINED MACHINE LEARNING MODEL 70
COMMUNICATION LATENCY 96
FIRST SUBSET 52
SECOND SUBSET 54
REMOTE PROCESSING RESULT 64
FIRST INSTRUCTION GENERATION FUNCTION 66
SECOND INSTRUCTION GENERATION FUNCTION 68
FIRST CONTROL INSTRUCTIONS 60
SECOND CONTROL INSTRUCTIONS 62
PROCESSOR 12
MEMORY 14
COMPUTING DEVICE 10

FIG. 5

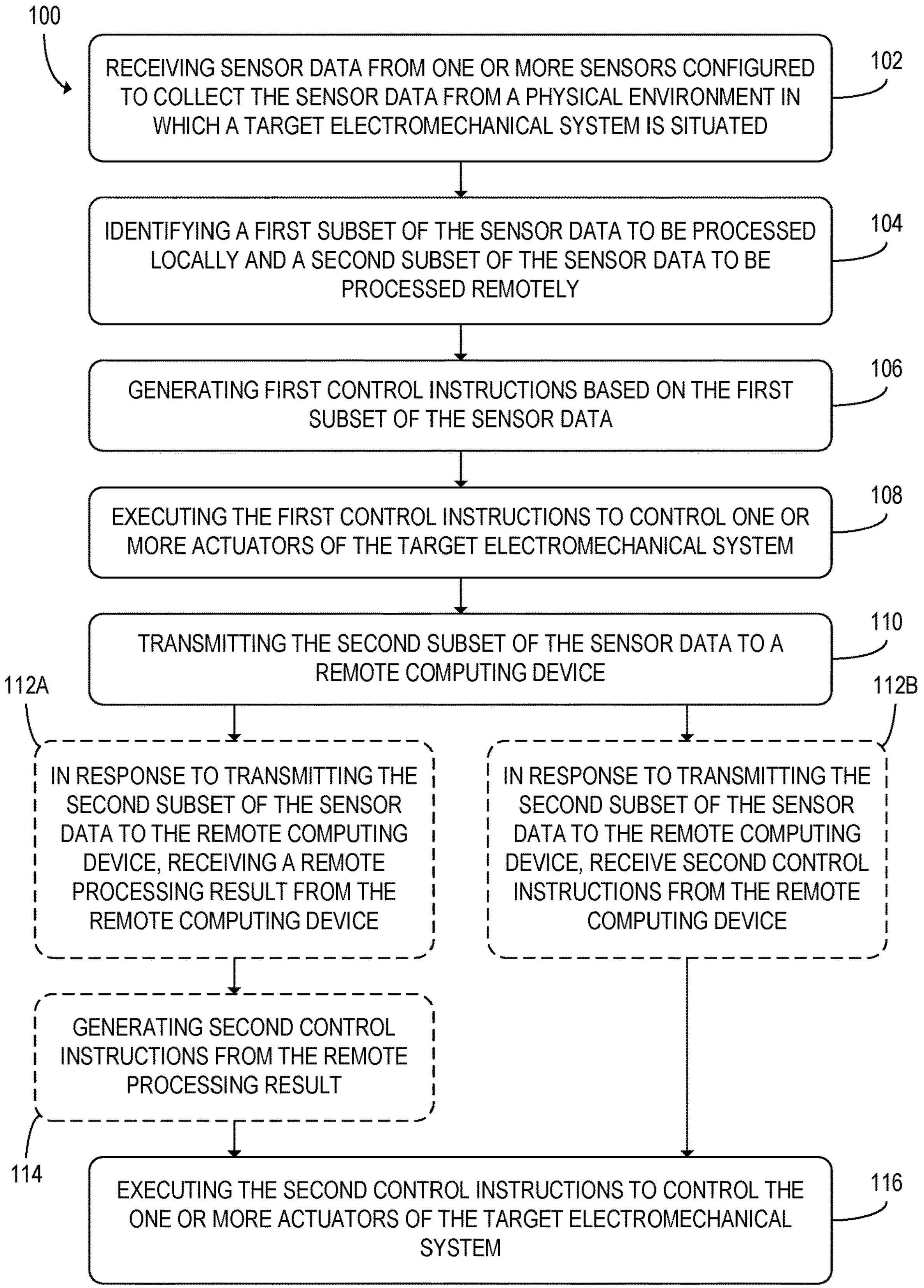
100
RECEIVING SENSOR DATA FROM ONE OR MORE SENSORS CONFIGURED TO COLLECT THE SENSOR DATA FROM A PHYSICAL ENVIRONMENT IN WHICH A TARGET ELECTROMECHANICAL SYSTEM IS SITUATED
102
IDENTIFYING A FIRST SUBSET OF THE SENSOR DATA TO BE PROCESSED LOCALLY AND A SECOND SUBSET OF THE SENSOR DATA TO BE PROCESSED REMOTELY
104
GENERATING FIRST CONTROL INSTRUCTIONS BASED ON THE FIRST SUBSET OF THE SENSOR DATA
106
EXECUTING THE FIRST CONTROL INSTRUCTIONS TO CONTROL ONE OR MORE ACTUATORS OF THE TARGET ELECTROMECHANICAL SYSTEM
108
TRANSMITTING THE SECOND SUBSET OF THE SENSOR DATA TO A REMOTE COMPUTING DEVICE
110
112A
IN RESPONSE TO TRANSMITTING THE SECOND SUBSET OF THE SENSOR DATA TO THE REMOTE COMPUTING DEVICE, RECEIVING A REMOTE PROCESSING RESULT FROM THE REMOTE COMPUTING DEVICE
112B
IN RESPONSE TO TRANSMITTING THE SECOND SUBSET OF THE SENSOR DATA TO THE REMOTE COMPUTING DEVICE, RECEIVE SECOND CONTROL INSTRUCTIONS FROM THE REMOTE COMPUTING DEVICE
GENERATING SECOND CONTROL INSTRUCTIONS FROM THE REMOTE PROCESSING RESULT
114
EXECUTING THE SECOND CONTROL INSTRUCTIONS TO CONTROL THE ONE OR MORE ACTUATORS OF THE TARGET ELECTROMECHANICAL SYSTEM
116

FIG. 6A

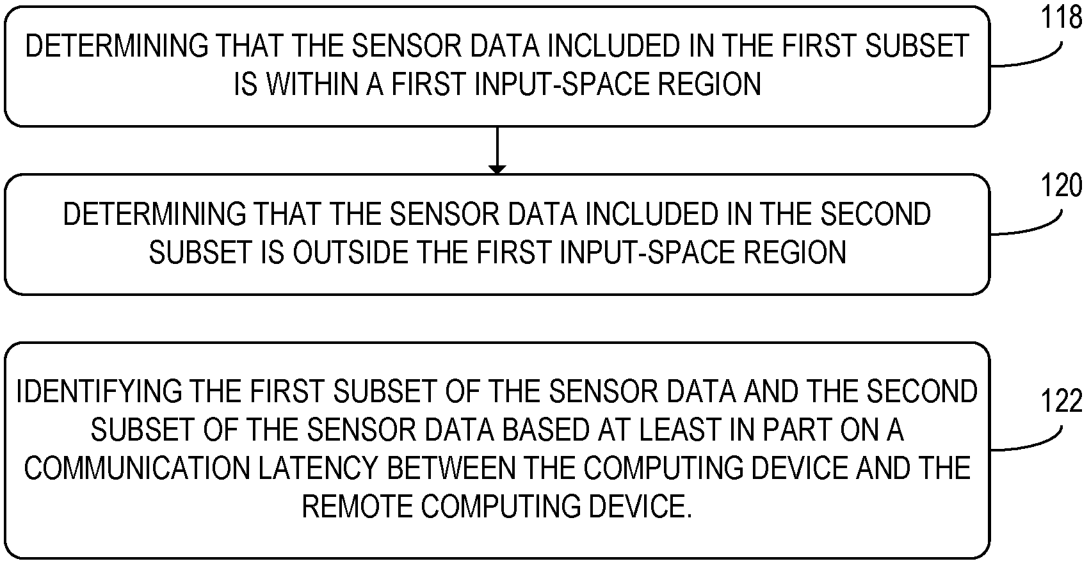
DETERMINING THAT THE SENSOR DATA INCLUDED IN THE FIRST SUBSET IS WITHIN A FIRST INPUT-SPACE REGION
118
DETERMINING THAT THE SENSOR DATA INCLUDED IN THE SECOND SUBSET IS OUTSIDE THE FIRST INPUT-SPACE REGION
120
IDENTIFYING THE FIRST SUBSET OF THE SENSOR DATA AND THE SECOND SUBSET OF THE SENSOR DATA BASED AT LEAST IN PART ON A COMMUNICATION LATENCY BETWEEN THE COMPUTING DEVICE AND THE REMOTE COMPUTING DEVICE.
122

FIG. 6B

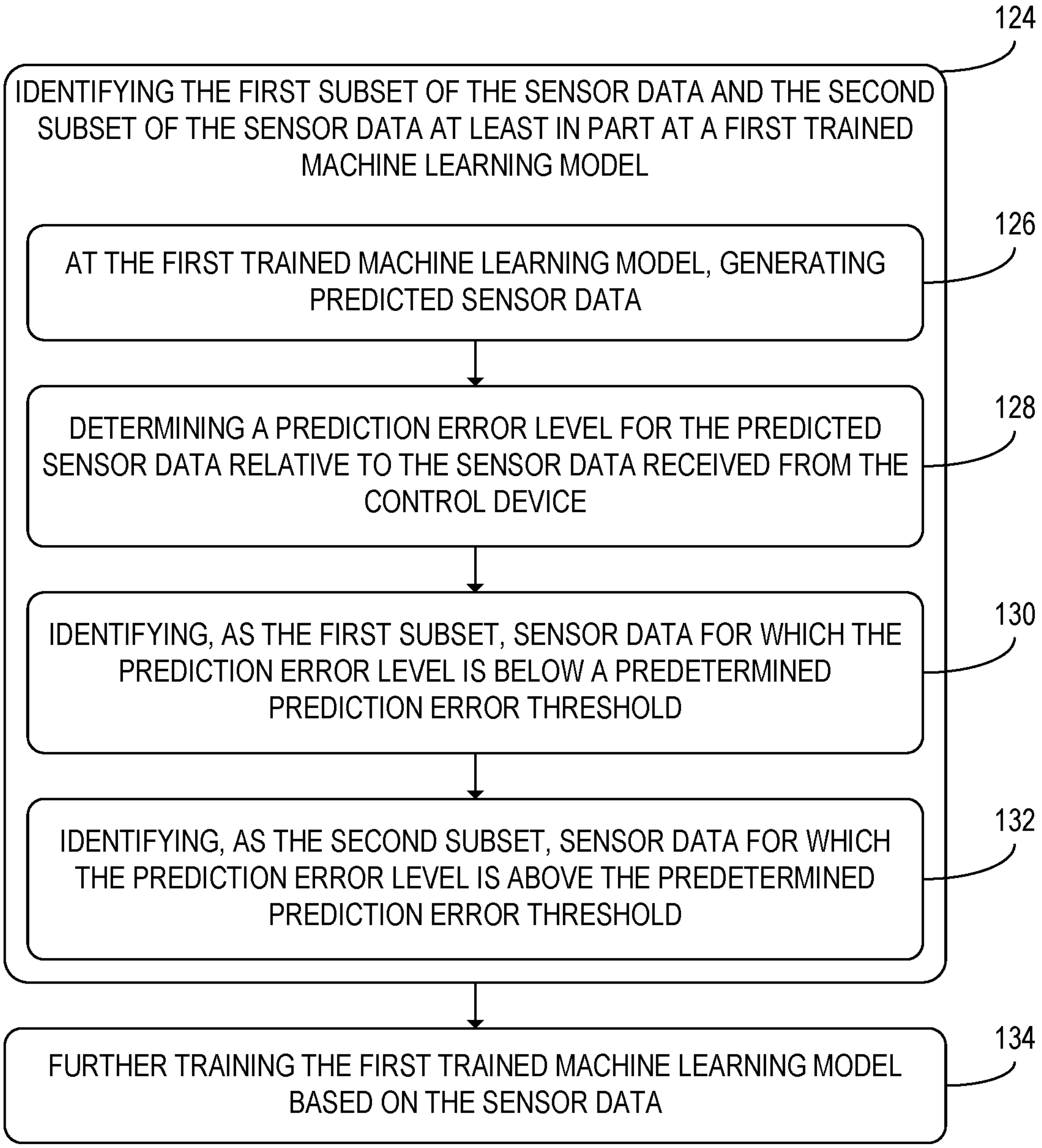
124
IDENTIFYING THE FIRST SUBSET OF THE SENSOR DATA AND THE SECOND SUBSET OF THE SENSOR DATA AT LEAST IN PART AT A FIRST TRAINED MACHINE LEARNING MODEL
126
AT THE FIRST TRAINED MACHINE LEARNING MODEL, GENERATING PREDICTED SENSOR DATA
128
DETERMINING A PREDICTION ERROR LEVEL FOR THE PREDICTED SENSOR DATA RELATIVE TO THE SENSOR DATA RECEIVED FROM THE CONTROL DEVICE
130
IDENTIFYING, AS THE FIRST SUBSET, SENSOR DATA FOR WHICH THE PREDICTION ERROR LEVEL IS BELOW A PREDETERMINED PREDICTION ERROR THRESHOLD
132
IDENTIFYING, AS THE SECOND SUBSET, SENSOR DATA FOR WHICH THE PREDICTION ERROR LEVEL IS ABOVE THE PREDETERMINED PREDICTION ERROR THRESHOLD
134
FURTHER TRAINING THE FIRST TRAINED MACHINE LEARNING MODEL BASED ON THE SENSOR DATA

FIG. 6C

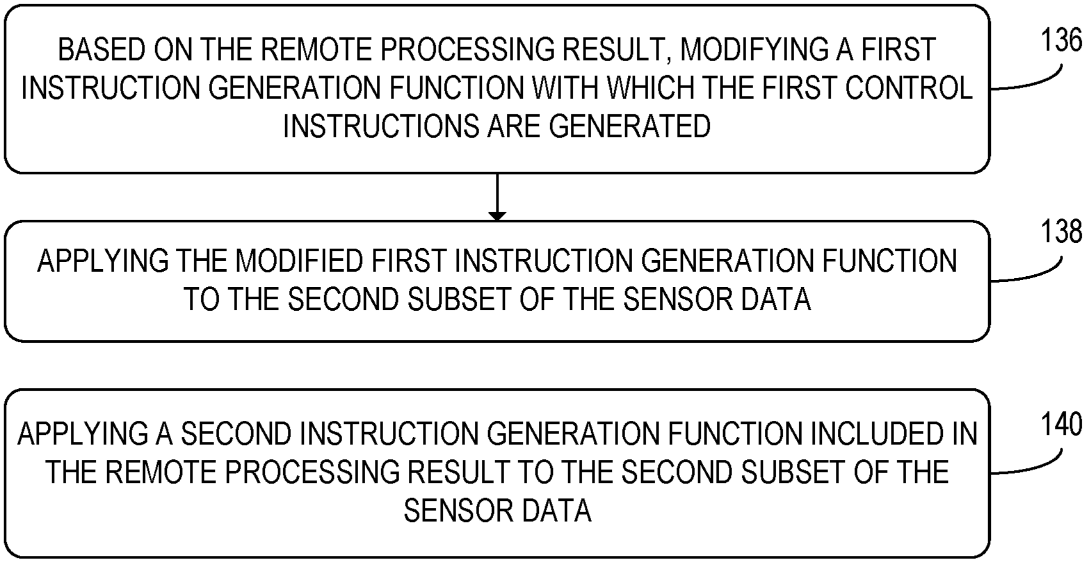
BASED ON THE REMOTE PROCESSING RESULT, MODIFYING A FIRST INSTRUCTION GENERATION FUNCTION WITH WHICH THE FIRST CONTROL INSTRUCTIONS ARE GENERATED
136
APPLYING THE MODIFIED FIRST INSTRUCTION GENERATION FUNCTION TO THE SECOND SUBSET OF THE SENSOR DATA
138
APPLYING A SECOND INSTRUCTION GENERATION FUNCTION INCLUDED IN THE REMOTE PROCESSING RESULT TO THE SECOND SUBSET OF THE SENSOR DATA
140

FIG. 6D

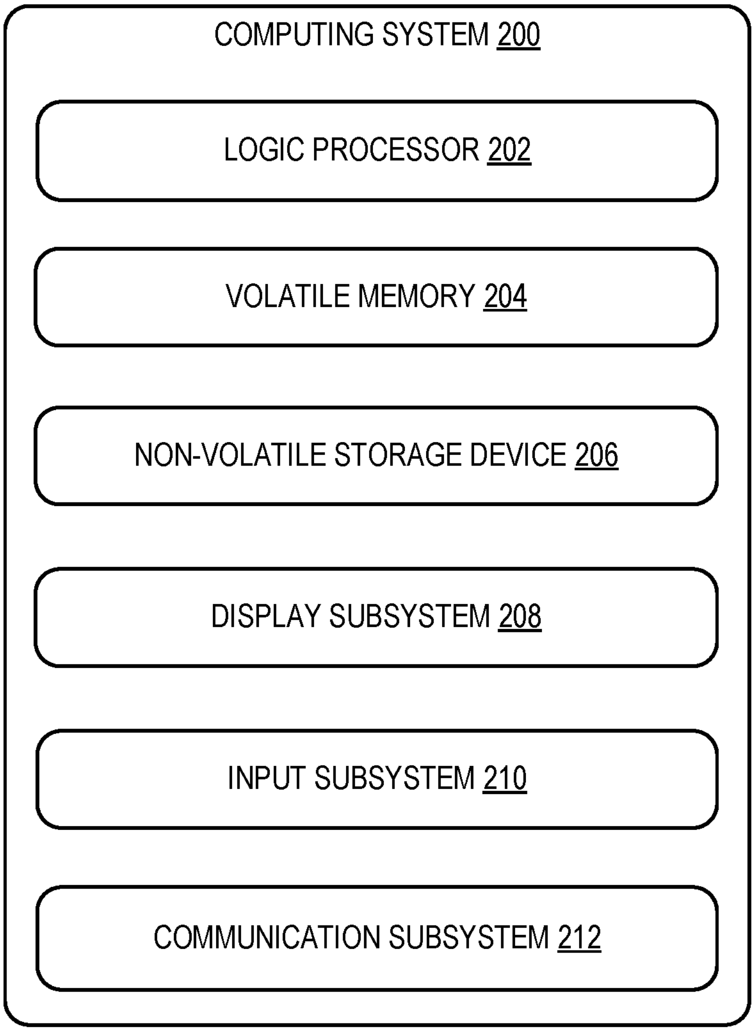
COMPUTING SYSTEM 200
LOGIC PROCESSOR 202
VOLATILE MEMORY 204
NON-VOLATILE STORAGE DEVICE 206
DISPLAY SUBSYSTEM 208
INPUT SUBSYSTEM 210
COMMUNICATION SUBSYSTEM 212

FIG. 7

EDGE COMPUTING DEVICE FOR CONTROLLING ELECTROMECHANICAL SYSTEM OR ELECTRONIC DEVICE WITH LOCAL AND REMOTE TASK DISTRIBUTION CONTROL

CROSS REFERENCE TO RELATED APPLICATION

This patent application is a continuation-in-part of and claims priority to U.S. patent application Ser. No. 17/077,976, entitled EDGE COMPUTING DEVICE FOR CONTROLLING ELECTROMECHANICAL SYSTEM WITH LOCAL AND REMOTE TASK DISTRIBUTION CONTROL, filed Oct. 22, 2020, the entire disclosure of which is hereby incorporated herein by reference.

BACKGROUND

Internet of Things (IoT) connected devices have recently come to be used in a wide variety of settings, such as manufacturing, transportation, resource extraction, climate control for buildings, and biometrics. These IoT connected devices may include sensors with which the IoT connected devices collect data related to the physical environments in which they are located. In addition, IoT connected devices may include controllable devices that are configured to perform physical actions in response to receiving control signals. The IoT connected device may be configured to communicate with a programmable logic controller (PLC), which may be configured to communicate with an edge computing device. The edge computing device may be configured to communicate with a remotely located server computing device, which may provide cloud computing resources to the edge computing device.

SUMMARY

According to one aspect of the present disclosure, a computing device is provided, including a processor configured to receive sensor data from a control device. The control device may include a control processor configured to execute control instructions to control an actuator of a target electromechanical system. The control device may further include one or more sensors configured to collect the sensor data from a physical environment in which the target electromechanical system is situated. The processor may be further configured to identify a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely. The processor may be further configured to generate first control instructions based on the first subset of the sensor data. The processor may be further configured to transmit the first control instructions to the control processor of the control device. The processor may be further configured to transmit the second subset of the sensor data to a remote computing device. In response to transmitting the second subset of the sensor data to the remote computing device, the processor may be further configured to receive a remote processing result from the remote computing device. The processor may be further configured to generate second control instructions from the remote processing result and transmit the second control instructions to the control processor of the control device.

This Summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This Summary is not intended to identify key features or essential features of the

claimed subject matter, nor is it intended to be used to limit the scope of the claimed subject matter. Furthermore, the claimed subject matter is not limited to implementations that solve any or all disadvantages noted in any part of this disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1**A schematically shows a computing system including a computing device connected to a remote computing device such as a server via a remote connection over a computer network such as a wide area network, and also connected to one or more sensors and a target electromechanical system via a local connection such as a serial, fieldbus, or LAN connection, according to one example embodiment.

FIG. **1**B shows the computing device of FIG. **1**A in an example in which the computing device is configured to control a plurality of robotic devices.

FIG. **2** shows the task distribution module executed by the processor of the computing device in additional detail, according to the embodiment of FIG. **1**A.

FIG. **3** shows an example parameter space diagram for sensor inputs, according to the embodiment of FIG. **1**A.

FIG. **4**A schematically shows the computing device when a predictive processing model is executed, according to the embodiment of FIG. **1**A.

FIG. **4**B shows sensor data and predicted sensor data when the predictive processing model of FIG. **4**A is executed.

FIG. **5** schematically shows the computing device and the remote computing device when the remote processing result received at the computing device includes a second instruction generation function, according to the embodiment of FIG. **1**A.

FIG. **6**A shows a flowchart of a method for use with a computing device to control one or more actuators of a target electromechanical system, according to the embodiment of FIG. **1**A.

FIGS. **6**B-**6**C show additional steps of the method of FIG. **6**A that may be performed when the first subset of the sensor data to be processed locally and the second subset of the sensor data to be processed remotely are identified.

FIG. **6**D shows additional steps of the method of FIG. **6**A that may be performed when the second control instructions are generated.

FIG. **7** shows a schematic view of an example computing environment in which the computing device of FIG. **1**A may be enacted.

DETAILED DESCRIPTION

In the conventional IoT system discussed above, in which an IoT controlled device is controlled using a PLC that communicates with an edge computing device, communication latency between the PLC and the edge computing device may interfere with the operation of IoT controlled device. This latency may result in a low temporal resolution for signals transmitted to and from the IoT controlled device and may limit what types of control schemes may be used. Limitations on the bandwidth of communications between the PLC and the edge computing device may further limit the resolution of the data received from sensors and the control schemes that may be used in the control signals sent to controllable devices.

In order to address the above shortcomings of conventional IoT systems, a computing system **1** including a computing device **10** is provided, as schematically shown in the example of FIG. **1**A. The computing device **10** of FIG. **1**A may include a processor **12**. In addition, the computing device **10** may include memory **14**, which may include volatile memory and non-volatile memory. The computing device **10** may be configured to transmit control instructions to a target electromechanical system **30**. The computing device **10** may be located proximate to the target electromechanical system **30** in the physical environment and may communicate with the target electromechanical system **30** via a wired or wireless local connection. The wired or wireless local connection is typically a serial connection (e.g., universal serial bus (USB), RS-232), fieldbus connection (e.g., GPIB, MAP, MMS, MODBUS, PROFIBUS, INTERBUS, CAN, etc.), local area network (LAN) connection (e.g., wired LAN over Ethernet/IP or wireless LAN), or other suitable local connection that does not include a high latency computer network such as a wide area network (WAN). The target electromechanical system may include, to name a few examples, a robot, HVAC system, alarm system, plumbing system, conveyor system, manufacturing applicator, or other controlled system. These examples are not to be considered limiting as numerous other examples are possible. The computing device **10** may be referred to as an edge computing device due to its position on the network topology having a local connection to the target electromechanical system **30** and a remote connection to a remote computing device **40**, described below.

The processor **12** of the computing device **10** may be configured to execute control instructions to control one or more actuators **32** included in the target electromechanical system **30**. The one or more actuators **32** may be one or more components of the target electromechanical system **30** that are configured to move when they receive electrical signals. For example, the one or more actuators **32** may include one or more motors, one or more speakers, one or more electrically controllable switches, or one or more other types of actuators. One or more controllable components other than actuators, such as one or more heating coils, lights, cameras, conveyors, valves, etc., may be included in the target electromechanical system **30** in some examples.

The processor **12** may be further configured to receive sensor data **50** from one or more sensors **26** configured to collect the sensor data **50** from a physical environment **20** in which the target electromechanical system **30** is situated. Although the one or more sensors **26** are shown in FIG. **1**A as being provided separately from the target electromechanical system **30**, the one or more sensors **26** may be integrated into the target electromechanical system **30** in other examples. The one or more sensors **26** may, for example, include one or more cameras, one or more temperature sensors, one or more accelerometers, one or more pressure sensors, one or more microphones, one or more magnetic field sensors, or one or more other types of sensors. The processor **12** may be configured to receive the sensor data **50** via a local connection selected from the group consisting of a serial connection, a fieldbus, and a local area network.

Subsequently to receiving the sensor data **50** from the one or more sensors **26**, the processor **12** may be further configured to identify a first subset **52** of the sensor data **50** to be processed locally and a second subset **54** of the sensor data **50** to be processed remotely. As discussed in further detail below, the second subset **54** may be transmitted to a remote computing device **40**. In some examples, the first subset **52** and the second subset **54** may overlap, whereas in other examples, the first subset **52** and the second subset **54** may be disjoint.

FIG. **1**B shows the computing device **10** in an example in which the computing device **10** is used with two target electromechanical systems **30** in the form of two robotic arms. In the example of FIG. **1**B, each of the target electromechanical systems **30** includes two actuators **32** configured to receive control instructions from the computing device **10**. The actuators **32** in the example of FIG. **1**B are each motor configured to move joints of the robotic arms. In addition, each of the robotic arms includes two sensors **26** that are configured to transmit sensor data **50** to the computing device **10**. For example, the sensors **26** included in each of the robotic arms may be accelerometers. The computing device **10** in the example of FIG. **1**B is configured to communicate with the remote computing device **40** over a network **46**.

The processor **12** of the computing device **10** may be configured to execute a task distribution module **56** configured to perform local and remote task distribution control, by identifying tasks or data associated with tasks that are to be processed locally at computing device **10** or remotely at remote computing device **40**. Thus, the task distribution control model **56** is configured to identify the first subset **52** (processed locally) and the second subset **54** (processed remotely) of the sensor data **50**. The task distribution module **56** may include a first trained machine learning model **70**. Additionally or alternatively, the task distribution module **56** may include one or more task distribution rules **71** that may be applied to the sensor data **50** to sort the sensor data **50** into the first subset **52** and the second subset **54**.

FIG. **2** shows the task distribution model **56** in additional detail. As shown in FIG. **2**, when the processor **12** executes the task distribution model **56**, the processor **12** may be further configured to identify a first task set **63** including one or more processing tasks **61** that are configured to be performed on the first subset **52** of the sensor data **50** and a second task set **65** including one or more processing tasks **61** that are configured to be performed on the second subset **54** of the sensor data **50**. When the processor **12** transmits the second subset **54** of the sensor data **50** to the remote processing device **40**, the processor **12** may be further configured to transmit an indication of the second processing set **65** to the remote processing device **40**. Alternatively, the one or more processing tasks **61** included in the second processing set **65** may be identified at the remote computing device **40**.

The processor **12** may be configured to sort the sensor data **50** into the first subset **52** and the second subset **54** based at least in part on one or more system conditions **55**, one or more task properties **57**, or one or more performance criteria **58**. The one or more system conditions **55** are properties of the computing device **10** that may affect computing performance. For example, the one or more system conditions **55** may include a local processor load **55**A of the processor **12**, a memory capacity **55**B of the memory **14**, or a network latency **55**C of a network connection between the computing device **10** and the remote computing device **40**. The one or more task properties **57** may be properties of the one or more processing tasks **61** included in the first task set **63** or the second task set **65**. For example, the one or more task properties **57** may include one or more of an estimated processing cost **57**A, an estimated memory usage **57**B, and an estimated network usage **57**C. The one or more task properties **57** may be indicated for one or more processing tasks **61** included in the first task set **63** or the second task set **65**. The one or more performance criteria **58** may, for example, include one or more respective task priority levels **58**A for the one or more processing tasks

61. The one or more performance criteria **58** may additionally or alternatively include one or more latency criteria **58**B, which may indicate one or more maximum allowed network latencies for the one or more processing tasks **61**. Additionally or alternatively to the system conditions **55**, task properties **57**, and performance criteria **58** provided in the above examples, other conditions or settings may be used as inputs by the task distribution module **56** when determining the first subset **52** and the second subset **54** of the sensor data **50**.

In some examples, as discussed above, the processor **12** may be configured to identify the first subset **52** of the sensor data **50** and the second subset **54** of the sensor data **50** at least in part at a first trained machine learning model **70**. For example, the first trained machine learning model **70** may be a recurrent neural network. The first trained machine learning model **70** may be configured to receive one or more values of the sensor data **50** as input, and may be configured to output one or more respective classifications for the one or more input values that classify the one or more input values as being included in the first subset **52** or the second subset **54**.

In some examples, as shown in the example parameter space diagram **80** of FIG. **3**, the processor **12** may be configured to identify the first subset **52** of the sensor data **50** at least in part by determining that the sensor data **50** included in the first subset **52** is within a first input-space region **82**. The first input-space region **82** is a region of a parameter space defined by the variables of the sensor data **50** received from the one or more sensors **26**. The parameter space may have a respective dimension for each dimension of the sensor data **50**. In the example of FIG. **3**, the variables of the sensor data **50** are a first motor speed and a second motor speed, which may, for example, be measured via imaging with one or more cameras. The processor **12** may be further configured to identify the second subset **54** of the sensor data **50** at least in part by determining that the sensor data **50** included in the second subset **54** is outside the first input-space region **82**. In the example parameter space diagram of FIG. **3**, the second subset **54** of the sensor data **50** is instead located within a second input-space region **84**. The first input-space region **82** may, for example, be a region of parameter space values that indicate that the target electromechanical system **30** is operating within a normal operating mode. In such examples, when the processor **12** identifies sensor data **50** located outside the first input-space region **82**, that sensor data **50** may indicate that the target electromechanical system **30** is operating under atypical conditions. Although the parameter space shown in the parameter space diagram **80** of FIG. **3** is a space with two variables, the parameter space may alternatively have some other number of variables.

In some examples in which the first subset **52** and the second subset **54** are identified at a first trained machine learning model **70**, the first trained machine learning model **70** may be a predictive processing model, as shown in the example of FIGS. **4**A-**4**B. FIG. **4**A schematically shows the computing device **10** when a predictive processing model is executed. As depicted in FIG. **4**A, the processor **12** may be configured to generate predicted sensor data **90** at the first trained machine learning model **70**. The sensor data **50** and the predicted sensor data **90** are shown in additional detail in FIG. **4**B. As shown in FIG. **4**B, the sensor data **50** may include respective values **53** for each of one or more variables **51**. Each of those values **53** may be associated with a respective time value **55** at which that value **53** was measured. The predicted sensor data **90** may include one or more predicted values **93** of the sensor data **50**. The one or more predicted values **93** may be associated with one or more time values **55** at which the one or more respective values **53** of the one or more variables **51** included in the sensor data **50** are predicted to match those predicted values **93**. When sensor data **50** is received for those one or more time values **55**, the processor **12** may be further configured to determine a prediction error level **92** for the predicted sensor data **90** relative to the sensor data **50** received from the one or more sensors **26** at that time value **55**. For example, the prediction error level **92** may be a mean squared error for the one or more predicted values **93** of the predicted sensor data **90**. In some examples, the processor **12** may be configured to determine the prediction error level **92** for a time interval including a plurality of time values **55**.

Returning to FIG. **4**A, the processor **12** may be further configured to identify, as the first subset **52**, sensor data **50** below a predetermined prediction error threshold **94**, and identify, as the second subset **54**, sensor data **50** above the predetermined prediction error threshold **94**. Thus, sensor data **50** that is accurately predicted by the first trained machine learning model **70** may be processed locally, while sensor data **50** that exhibits high levels of prediction error may be transmitted to the remote computing device **40** for processing.

In some examples, when the sensor data **50** and the predicted sensor data **90** each have a dimensionality of two (as one particular example) or greater, the processor **12** may be configured to compute respective prediction error levels **92** for one or more subsets of the plurality of variables **51**. For example, the processor **12** may be configured to compute respective prediction error levels **92** for each of the measured variables **51** individually, or for one or more subsets of the plurality of variables **51** that include two or more variables **51**. The processor **12** may be further configured to compare the prediction error levels **92** for each of those subsets of the plurality of variables **51** to a respective predetermined prediction error threshold **94**. For each subset of the plurality of variables that exceeds its corresponding predetermined prediction error threshold **94**, the one or more variables in that subset may be transmitted to the remote computing device **40**. The other variables **51** of the plurality of variables **51** may be processed locally.

In examples in which the first subset **52** of the sensor data **50** and the second subset **54** of the sensor data **50** are selected at a first trained machine learning model **70**, the processor **12** may be further configured to further train the first trained machine learning model **70** based on the sensor data **50**. In examples in which the processor **12** is configured to generate predicted sensor data **90** at the first trained machine learning model **70**, the processor **12** may be further configured to modify the first trained machine learning model **70** when sensor data **50** is received. Such a modification may be made based on the prediction error level **92** for that sensor data **50**. For example, when the first trained machine learning model is configured to generate predicted sensor data **90**, the first trained machine learning model may be initially trained via unsupervised learning using a set of training sensor data and may be further updated via unsupervised learning using the sensor data **50**.

Returning to FIG. **1**A, the processor **12** may be further configured to generate first control instructions **60** based on the first subset **52** of the sensor data **50**. Subsequently to generating the first control instructions **60**, the processor **12** may be further configured to execute the first control instructions **60** to control the one or more actuators **32** of the target electromechanical system **30**. The first control instructions

60 may be instructions to perform one or more control operations at the one or more actuators **32** included in the target electromechanical system **30**. The first control instructions **60** may, for example, be an instruction to start, stop, or change the direction of a motor; to open or close an electromechanical switch; to play a sound on a speaker; or perform some other operation at the one or more actuators **32** of the target electromechanical system **30**. These examples are to be considered illustrative and not limiting as numerous functions are possible.

The first control instructions **60** may be generated at an instruction generation module **59**, which may include a second trained machine learning model **72**. Additionally or alternatively, the instruction generation module **59** may include one or more instruction generation rules **73**. As shown in the example of FIG. **5**, the processor **12** may be configured to apply a first instruction generation function **66** to the first subset of the sensor data **50** to compute the first control instructions **60**. In examples in which the processor **12** is configured to generate the first control instructions **60** at least in part at a second trained machine learning model **72**, the second trained machine learning model **72** may, for example, be a recurrent neural network.

The processor **12** may be further configured to transmit the second subset **54** of the sensor data **50** to a remote computing device **40**. For example, the processor **12** may be configured to transmit the second subset **54** of the sensor data **50** to the remote computing device **40** via a wide area network (WAN). The remote computing device **40** may include a remote processor **42** and remote memory **44**. The functionality of the remote computing device **40** may be distributed between a plurality of remote computing devices **40** configured to communicate with each other. In some examples, the remote computing device **40** may be a server computing device located in a data center.

In response to transmitting the second subset **54** of the sensor data **50** to the remote computing device **40**, the processor **12** may be further configured to receive a remote processing result **64** from the remote computing device **40**. The processor **12** may be further configured to generate second control instructions **62** from the remote processing result **64** and execute the second control instructions **62** to control the one or more actuators **32** of the target electromechanical system **30**. Alternatively, the processor **12** may be configured to receive the second control instructions **62** from the remote computing device **40** as the remote processing result **64**.

In some examples, the remote processing result **64** may include additional sensor data received at the remote computing device **40** via one or more other computing devices. The one or more other computing devices may be connected to one or more additional sensors located in the physical environment **20**. In such examples, the second control instructions **62** may be generated based on the additional sensor data. Thus, the additional sensor data may be used as contextual sensor data that provides the processor **12** with additional information about the physical environment **20** in which is it located. The additional sensor data may, for example, indicate that a temperature measured by an additional sensor connected to another computing device is close to the top of a safe operating temperature range. In response to receiving a remote processing result **64** that includes the temperature measurement, the processor **12** may be configured to generate and execute second control instructions **62** to turn on a fan.

In some examples, the remote processing result **64** may include an indication of the second input-space region **84** within which the sensor data **50** included in the second subset **54** is located. The remote processing result **64** may further include, as shown in FIG. **5**, a second instruction generation function **68** that maps one or more sensor data values **53** located within the second input-space region **84** to one or more respective control instructions. In such examples, the processor **12** may be further configured to generate the second control instructions **62** at least in part by applying the second instruction generation function **68** to the second subset **54** of the sensor data **50**. The processor **12** may be further configured to store the second instruction generation function **68** in the memory **14**. Thus, as the processor **12** receives sensor data **50** located within new regions of the parameter space, the area of the parameter space for which control instructions are generated without offloading processing to the remote computing device **40** may expand.

Additionally or alternatively to including a second instruction generation function **68**, the remote processing result **64** may include a modification to the first instruction generation function **66** with which the processor is configured to generate the first control instructions **60**. For example, when the first instruction generation function is a second trained machine learning model **72**, the modification to the first instruction generation function **66** may be additional training performed at the second trained machine learning model **72**.

The remote computing device **40** may be configured to generate the remote processing result **64** at a remote instruction generation module **75**, as shown in the example of FIG. **1A**. The remote instruction generation module **75** may include a remote machine learning model **76**. Additionally or alternatively, the remote instruction generation module **75** may include one or more remote instruction generation rules **76**. The sensor data **50** included in the second subset **54** may be used as input for the remote machine learning model **74** or the one or more remote instruction generation rules **76** included in the remote instruction generation module **75**. The remote machine learning model **74** or the one or more remote instruction generation rules **76** may additionally take as input the additional sensor data received from the one or more other computing devices. In examples in which the first trained machine learning model **70** is a predictive processing model, as shown in the example of FIG. **4A**, the remote machine learning model **74** may be further configured to receive the prediction error level **92** for the predicted sensor data **90**. In other examples, the remote machine learning model **74** may be a version of the second trained machine learning model **72** with additional training and/or additional model parameters.

In some examples, the processor **12** may be configured to generate the first control instructions **60** based on the first subset **52** of the sensor data **50** in real time as the first subset **52** is received. The processor **12** may be further configured to transmit the second subset **54** of the sensor data **50** to the remote computing device **40** for non-real-time processing. Thus, real-time control of the one or more actuators **32** may be performed at the computing device **10** with low latency, whereas other processing tasks may be performed at the remote computing device **40** with higher latency but increased processing power. It will be appreciated that the connection between the computing device **10** and the remote computing device **40** is typically over a WAN.

In some examples, as shown in the example of FIG. **5**, the processor **12** may be configured to identify the first subset **52** of the sensor data **50** and the second subset **54** of the sensor data **50** based at least in part on a communication latency **96** between the processor **12** and the remote computing device **40**. For example, the processor **12** may be configured to compute a latency threshold **98** based on the sensor data **50** in real time as the sensor data is received. The latency threshold **98** may be determined at the first trained machine learning model **70**. When the latency threshold **98** is below the communication latency between the processor **12** and the remote computing device **40**, the processor **12** may be further configured to compute first control instructions **60** locally based on the sensor data **50**. When the latency threshold **98** is above the communication latency **96**, the processor **12** may be further configured to transmit at least a portion of the sensor data **50** to the remote computing device **40** for processing. Thus, the processor **12** may be configured to determine control instructions locally when the sensor data **50** indicates urgent conditions and to transmit sensor data **50** to the remote computing device **40** for processing when the sensor data **50** does not indicate urgent conditions. The first subset **52** and the second subset **54** may be identified based at least in part on the communication latency **96** in examples in which the remote machine learning model **74** is a version of the second trained machine learning model **72** with more model parameters.

FIG. **6**A shows a flowchart of a method **100** for use with a computing device. The method **100** of FIG. **6**A may be performed at the computing device **10** of FIG. **1**A or at some other computing device. At step **102**, the method **100** may include receiving sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electromechanical system is situated. For example, the sensor data may be received from one or more cameras, one or more temperature sensors, one or more accelerometers, one or more pressure sensors, one or more microphones, one or more magnetic field sensors, or one or more other types of sensors. The computing device may be located in the physical environment in which the one or more sensors are provided and may receive the sensor data via a wired or wireless connection such as a LAN.

At step **104**, the method **100** may further include identifying a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely. The first subset and the second subset may be identified based on the values of the sensor data. Additionally, or alternatively, the first subset and the second subset may be identified based at least in part on one or more system conditions of the computing device, one or more task properties of processing tasks associated with the first subset and the second subset, or one or more performance criteria for the computing device or a remote computing device at which the second subset of the sensor data is configured to be processed.

FIG. **6**B shows additional steps of the method **100** that may be performed when performing step **104**. At step **118**, step **104** may include determining that the sensor data included in the first subset is within a first input-space region. In addition, at step **120**, step **104** may further include determining that the sensor data included in the second subset is outside the first input-space region. The first input-space region may be a region of a parameter space formed by the one or more variables measured by the one or more sensors.

In some examples, at step **122**, step **104** may include identifying the first subset of the sensor data and the second subset of the sensor data based at least in part on a communication latency between the computing device and the remote computing device. In such examples, the communication latency may be compared to a latency threshold that is dynamically computed in real time at the computing device and indicates how time-sensitive the sensor data is. The first subset may be a subset of the sensor data for which the latency threshold is below the communication latency (indicating that the sensor data has high time sensitivity), and the second subset may be a subset of the sensor data for which the latency threshold is above the communication latency (indicating that the sensor data has low time sensitivity).

FIG. **6**C also shows additional steps of the method **100** that may be performed when step **104** is performed. At step **124**, the method **100** may include identifying the first subset of the sensor data and the second subset of the sensor data at least in part at a first trained machine learning model. The first trained machine learning model may, for example, be a recurrent neural network. The first trained machine learning model may take the sensor data as an input and may output respective classifications for the sensor data values as being included in the first subset or the second subset.

In some examples, at step **126**, step **124** may include generating predicted sensor data at the first trained machine learning model. The predicted sensor data may be time series data. In addition, at step **128**, step **124** may further include determining a prediction error level for the predicted sensor data relative to the sensor data received from the one or more sensors. Separate prediction error levels may, in some examples, be determined for individual variables of the sensor data or for one or more subsets of a plurality of variables included in the sensor data. In other examples, one prediction error level may be determined for the sensor data at a corresponding time value or time interval. At step **130**, step **124** may further include identifying, as the first subset, sensor data for which the prediction error level is below a predetermined prediction error threshold. In addition, at step **132**, step **124** may further include identifying, as the second subset, sensor data for which the prediction error level is above the predetermined prediction error threshold.

In some examples in which step **124** is performed, the method **100** may further include, at step **134**, further training the first trained machine learning model based on the sensor data. For example, when the first machine learning model is a predictive processing model configured to generate predicted sensor data, the first machine learning model may be further trained via online learning as it receives sensor data, and may thereby increase the accuracy of the predicted sensor data it generates.

Returning to FIG. **6**A, the method **100** may further include, at step **106**, generating first control instructions based on the first subset of the sensor data. In some examples, the first control instructions may be generated at least in part at a second trained machine learning model. At step **108**, the method **100** may further include executing the first control instructions to control one or more actuators of the target electromechanical system. Thus, instructions based on the first subset of the sensor data may be used to control the one or more actuators without incurring delays that would result from communicating with the remote computing device.

At step **110**, the method **100** may further include transmitting the second subset of the sensor data to a remote computing device. The second subset may be transmitted to the remote computing device via a WAN. In some examples, the method **100** may further include, at step **112**A, receiving a remote processing result from the remote computing device in response to transmitting the second subset of the sensor data to the remote computing device. In examples in which step **112**A is performed, the method **100** may further include, at step **114**, generating second control instructions from the remote processing result. In other examples, the method **100** may alternatively include, at step **112**B, receiving the second control instructions from the remote computing device in response to transmitting the second subset of the sensor data to the remote computing device.

At step **116**, the method **100** may further include executing the second control instructions to control the one or more actuators of the target electromechanical system. Thus, the remote processing result may be used to select actions performed at the one or more actuators.

FIG. **6**D shows additional steps of the method **100** that may be performed in some examples when the second control instructions are generated at step **114**. At step **136**, generating the second control instructions at step **114** may further include, based on the remote processing result, modifying a first instruction generation function with which the first control instructions are generated. In examples in which step **136** is performed, the method **100** may further include, at step **138**, applying the modified first instruction generation function to the second subset of the sensor data.

In some examples, the remote processing result may include a second instruction generation function. In such examples, step **114** may further include, at step **140**, applying the second instruction generation function included in the remote processing result to the second subset of the sensor data.

In one example use case scenario, the computing device may be used in a sewage treatment plant. In such an example, the processor of the computing device may be configured to receive sensor data indicating a flow rate for effluent through a line with flow rate controlled by a valve. The computing device may be configured to transmit control instructions to an actuator that controls the valve, thereby functioning as part of a flow control system. The computing device may be programmable with a set point for the flow rate through the line, and may be configured to transmit control signals to adjust the valve opening to control the effluent to the flow rate. When the flow rate deviates from the set point by an amount greater than a corresponding threshold, the computing device may transmit sensor data to a remote computing device for further processing. For example, the sensor data transmitted to the remote computing device may include the flow rate and valve position during a time interval starting at a predetermined amount of time before the time value at which the threshold was exceeded. The remote computing device may input the sensor data it receives into a remote machine learning model, which may generate control instructions that are transmitted back to the computing device. The computing device may execute those control instructions to control the actuators included in the valves, and may thereby restore the flow rate to normal levels.

In another example, the computing device of the example above may be configured to execute a task distribution rule that executes locally a local flow rate control task for a particular flow rate in a particular line as controlled by a particular valve as the target electromechanical system, and that sends the flow rate and valve position information to the remote machine learning model locally to execute a global flow control task, such providing drainage to a city sewer system while not overloading a downstream outlet channel. To execute the global control task, the remote machine learning model receives as inputs the flow rates and valve positions of other lines within the system, as well as the level of the outlet channel. In this manner, local control tasks are performed locally at the computing device, and remote control tasks are performed under the direction of the remote computing device, which takes into account a wider variety of information sources.

In another example, the computing device may be configured to receive images from a camera imaging a manufacturing line as a sensor locally, generate a downscaled lower resolution of the image, and process the lower resolution version of the image using a convolutional neural network (CNN) to output a first control instruction to a robot performing a weld on a target workpiece in the image. The CNN may be trained to perform rough defect detection identify a defect in the workpiece based on the lower resolution image and stop the welding operation by the robot in real time during the operation. The computing device may be configured to send a higher resolution version of the image to the remote computing device for processing, and a convolutional neural network at the remote computing device may be configured to detect fine defects in the higher resolution version of the image, and send an instruction to computing device to take a remedial action. The remedial action may be to control the robot to perform a second weld to repair the defect, or if the workpiece has moved on in the assembly process, to instruct a downstream manufacturing conveyor to route the workpiece back for repair or discard the workpiece due to the fine defect.

Using the devices and methods discussed above, one or more actuators included in an IoT connected device may be controlled while avoiding communication delays that would otherwise occur when a PLC communicates with an edge computing device. Since such communication delays may be avoided, the computing device may be provided with additional computing capabilities, such as implementation of machine learning models, that would not be available on a PLC. The computing device may also offload processing of some of the sensor data it receives to a remote computing device. For example, the remote computing device and the computing device may have a "brain-spinal cord" relationship in which computing tasks with low computing power requirements and high time sensitivity are performed at the computing device whereas tasks with high computing power requirements and low time sensitivity are performed at the remote computing device. Thus, the computing device may quickly and efficiently control the IoT controlled device while also being able to respond appropriately to a wide variety of sensor inputs.

In some embodiments, the methods and processes described herein may be tied to a computing system of one or more computing devices. In particular, such methods and processes may be implemented as a computer-application program or service, an application-programming interface (API), a library, and/or other computer-program product.

FIG. **7** schematically shows a non-limiting example of a computing system **200** that can enact one or more of the devices and methods described above. Computing system **200** is shown in simplified form. Computing system **200** may embody the computing device **10** described above and illustrated in FIG. **1**. Computing system **200** may take the form of one or more personal computers, server computers, tablet computers, home-entertainment computers, network computing devices, gaming devices, mobile computing devices, mobile communication devices (e.g., smart phone), and/or other computing devices, and wearable computing devices such as smart wristwatches and head mounted augmented reality devices.

Computing system **200** includes a logic processor **202** volatile memory **204**, and a non-volatile storage device **206**. Computing system **200** may optionally include a display subsystem **208**, input subsystem **210**, communication subsystem **212**, and/or other components not shown in FIG. **7**.

Logic processor **202** includes one or more physical devices configured to execute instructions. For example, the logic processor may be configured to execute instructions that are part of one or more applications, programs, routines, libraries, objects, components, data structures, or other logical constructs. Such instructions may be implemented to perform a task, implement a data type, transform the state of one or more components, achieve a technical effect, or otherwise arrive at a desired result.

The logic processor may include one or more physical processors (hardware) configured to execute software instructions. Additionally or alternatively, the logic processor may include one or more hardware logic circuits or firmware devices configured to execute hardware-implemented logic or firmware instructions. Processors of the logic processor **202** may be single-core or multi-core, and the instructions executed thereon may be configured for sequential, parallel, and/or distributed processing. Individual components of the logic processor optionally may be distributed among two or more separate devices, which may be remotely located and/or configured for coordinated processing. Aspects of the logic processor may be virtualized and executed by remotely accessible, networked computing devices configured in a cloud-computing configuration. In such a case, these virtualized aspects are run on different physical logic processors of various different machines, it will be understood.

Non-volatile storage device **206** includes one or more physical devices configured to hold instructions executable by the logic processors to implement the methods and processes described herein. When such methods and processes are implemented, the state of non-volatile storage device **206** may be transformed—e.g., to hold different data.

Non-volatile storage device **206** may include physical devices that are removable and/or built-in. Non-volatile storage device **206** may include optical memory (e.g., CD, DVD, HD-DVD, Blu-Ray Disc, etc.), semiconductor memory (e.g., ROM, EPROM, EEPROM, FLASH memory, etc.), and/or magnetic memory (e.g., hard-disk drive, floppy-disk drive, tape drive, MRAM, etc.), or other mass storage device technology. Non-volatile storage device **206** may include nonvolatile, dynamic, static, read/write, read-only, sequential-access, location-addressable, file-addressable, and/or content-addressable devices. It will be appreciated that non-volatile storage device **206** is configured to hold instructions even when power is cut to the non-volatile storage device **206**.

Volatile memory **204** may include physical devices that include random access memory. Volatile memory **204** is typically utilized by logic processor **202** to temporarily store information during processing of software instructions. It will be appreciated that volatile memory **204** typically does not continue to store instructions when power is cut to the volatile memory **204**.

Aspects of logic processor **202**, volatile memory **204**, and non-volatile storage device **206** may be integrated together into one or more hardware-logic components. Such hardware-logic components may include field-programmable gate arrays (FPGAs), program- and application-specific integrated circuits (PASIC/ASICs), program- and application-specific standard products (PSSP/ASSPs), system-on-a-chip (SOC), and complex programmable logic devices (CPLDs), for example.

The terms "module," "program," and "engine" may be used to describe an aspect of computing system **200** typically implemented in software by a processor to perform a particular function using portions of volatile memory, which function involves transformative processing that specially configures the processor to perform the function. Thus, a module, program, or engine may be instantiated via logic processor **202** executing instructions held by non-volatile storage device **206**, using portions of volatile memory **204**. It will be understood that different modules, programs, and/or engines may be instantiated from the same application, service, code block, object, library, routine, API, function, etc. Likewise, the same module, program, and/or engine may be instantiated by different applications, services, code blocks, objects, routines, APIs, functions, etc. The terms "module," "program," and "engine" may encompass individual or groups of executable files, data files, libraries, drivers, scripts, database records, etc.

When included, display subsystem **208** may be used to present a visual representation of data held by non-volatile storage device **206**. The visual representation may take the form of a graphical user interface (GUI). As the herein described methods and processes change the data held by the non-volatile storage device, and thus transform the state of the non-volatile storage device, the state of display subsystem **208** may likewise be transformed to visually represent changes in the underlying data. Display subsystem **208** may include one or more display devices utilizing virtually any type of technology. Such display devices may be combined with logic processor **202**, volatile memory **204**, and/or non-volatile storage device **206** in a shared enclosure, or such display devices may be peripheral display devices.

When included, input subsystem **210** may comprise or interface with one or more user-input devices such as a keyboard, mouse, touch screen, or game controller. In some examples, the input subsystem may comprise or interface with selected natural user input (NUI) componentry. Such componentry may be integrated or peripheral, and the transduction and/or processing of input actions may be handled on- or off-board. Example NUI componentry may include a microphone for speech and/or voice recognition; an infrared, color, stereoscopic, and/or depth camera for machine vision and/or gesture recognition; a head tracker, eye tracker, accelerometer, and/or gyroscope for motion detection and/or intent recognition; as well as electric-field sensing componentry for assessing brain activity; and/or any other suitable sensor.

When included, communication subsystem **212** may be configured to communicatively couple various computing devices described herein with each other, and with other devices. Communication subsystem **212** may include wired and/or wireless communication devices compatible with one or more different communication protocols. As non-limiting examples, the communication subsystem may be configured for communication via a wireless telephone network, or a wired or wireless local- or wide-area network. In some examples, the communication subsystem may allow computing system **200** to send and/or receive messages to and/or from other devices via a network such as the Internet.

The following paragraphs discuss several aspects of the present disclosure. According to one aspect of the present disclosure, a computing device is provided, including a processor configured to receive sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electromechanical system is situated. The processor may be further configured to identify a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely. The processor may be further configured to generate first control instructions based on the first subset of the sensor data. The processor may be further configured to execute the first control instructions to control one or more actuators of the target electromechanical system. The processor may be further configured to transmit the second subset of the sensor data to a remote computing device, and, in response to transmitting the second subset of the sensor data to the remote computing device, receive a remote processing result from the remote computing device. The processor may be further configured to generate second control instructions from the remote processing result. The processor may be further configured to execute the second control instructions to control the one or more actuators of the target electromechanical system.

According to this aspect, the processor may be configured to identify the first subset of the sensor data at least in part by determining that the sensor data included in the first subset is within a first input-space region. The processor may be further configured to identify the second subset of the sensor data at least in part by determining that the sensor data included in the second subset is outside the first input-space region.

According to this aspect, the remote processing result may include an indication of a second input-space region within which the sensor data included in the second subset is located. The remote processing result may further include a second instruction generation function that maps one or more sensor data values located within the second input-space region to one or more respective control instructions. The processor may be further configured to generate the second control instructions at least in part by applying the second instruction generation function to the second subset of the sensor data.

According to this aspect, the remote processing result may include a modification to a first instruction generation function with which the processor is configured to generate the first control instructions.

According to this aspect, the processor may be configured to identify the first subset of the sensor data and the second subset of the sensor data at least in part at a first trained machine learning model.

According to this aspect, the processor may be further configured to, at the first trained machine learning model, generate predicted sensor data. The processor may be further configured to determine a prediction error level for the predicted sensor data relative to the sensor data received from the one or more sensors. The processor may be further configured to identify, as the first subset, sensor data for which the prediction error level is below a predetermined prediction error threshold. The processor may be further configured to identify, as the second subset, sensor data for which the prediction error level is above the predetermined prediction error threshold.

According to this aspect, the processor may be further configured to further train the first trained machine learning model based on the sensor data.

According to this aspect, the processor may be configured to generate the first control instructions at least in part at a second trained machine learning model.

According to this aspect, the processor may be configured to generate the first control instructions based on the first subset of the sensor data in real time as the first subset is received. The processor may be further configured to transmit the second subset of the sensor data to the remote computing device for non-real-time processing.

According to this aspect, the processor may be configured to identify the first subset of the sensor data and the second subset of the sensor data based at least in part on a communication latency between the processor and the remote computing device.

According to this aspect, the processor may be configured to receive the sensor data via a local connection selected from the group consisting of a serial connection, a fieldbus, and a local area network. The processor may be configured to transmit the second subset of the sensor data to the remote computing device via a wide area network (WAN).

According to another aspect of the present disclosure, a method for use with a computing device is provided. The method may include receiving sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electromechanical system is situated. The method may further include identifying a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely. The method may further include generating first control instructions based on the first subset of the sensor data. The method may further include executing the first control instructions to control one or more actuators of the target electromechanical system. The method may further include transmitting the second subset of the sensor data to a remote computing device, and, in response to transmitting the second subset of the sensor data to the remote computing device, receiving a remote processing result from the remote computing device. The method may further include generating second control instructions from the remote processing result. The method may further include executing the second control instructions to control the one or more actuators of the target electromechanical system.

According to this aspect, identifying the first subset of the sensor data may include determining that the sensor data included in the first subset is within a first input-space region. Identifying the second subset of the sensor data may include determining that the sensor data included in the second subset is outside the first input-space region.

According to this aspect, generating the second control instructions may include, based on the remote processing result, modifying a first instruction generation function with which the first control instructions are generated. Generating the second control instructions may further include, applying the modified first instruction generation function to the second subset of the sensor data.

According to this aspect, the method may further include identifying the first subset of the sensor data and the second subset of the sensor data at least in part at a first trained machine learning model.

According to this aspect, the method may further include, at the first trained machine learning model, generating predicted sensor data. The method may further include determining a prediction error level for the predicted sensor data relative to the sensor data received from the one or more sensors. The method may further include identifying, as the first subset, sensor data for which the prediction error level is below a predetermined prediction error threshold. The method may further include identifying, as the second subset, sensor data for which the prediction error level is above the predetermined prediction error threshold.

According to this aspect, the first control instructions may be generated at least in part at a second trained machine learning model.

According to this aspect, the first control instructions may be generated in real time based on the first subset of the sensor data as the first subset of sensor data is received. The second subset of the sensor data may be transmitted to the remote computing device for non-real-time processing.

According to this aspect, the method may further include identifying the first subset of the sensor data and the second subset of the sensor data based at least in part on a communication latency between the computing device and the remote computing device.

According to another aspect of the present disclosure, a computing device is provided, including a processor configured to receive sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electromechanical system is situated. The processor may be further configured to identify a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely. The processor may be further configured to generate first control instructions based on the first subset of the sensor data. The processor may be further configured to execute the first control instructions to control one or more actuators of the target electromechanical system. The processor may be further configured to transmit the second subset of the sensor data to a remote computing device, and, in response to transmitting the second subset of the sensor data to the remote computing device, receive second control instructions from the remote computing device. The processor may be further configured to execute the second control instructions to control the one or more actuators of the target electromechanical system.

It will be understood that the configurations and/or approaches described herein are exemplary in nature, and that these specific embodiments or examples are not to be considered in a limiting sense, because numerous variations are possible.

For example, although the devices and methods of the present disclosure are discussed above with reference to an electromechanical system at which one or more actuators are controlled, the devices and methods discussed above may also be used with other electronic devices, such as a computing device. In such examples, one or more controllable components other than actuators may be controlled using by executing the first control instructions and the second control instructions. Such controllable components may, as discussed above, include one or more heating coils, lights, cameras, conveyors, valves.

One or more display devices included in the display subsystem **208** may also be included among the one or more controllable components. Thus, controlling the one or more controllable components may include presenting or modifying a GUI displayed to a user.

In some examples, controlling the one or more controllable components may additionally or alternatively include storing data in the non-volatile storage device **206**. In such examples, modifying the instruction generation function or further training the first trained machine learning model may be included among the steps performed when controlling the one or more controllable components. Other steps that include storing data in the non-volatile storage device **206** may additionally or alternatively be performed when controlling the one or more controllable components.

The one or more sensors from which the sensor data is received may, in some examples, be included in the input subsystem **210**. The one or more sensors may accordingly be provided in one or more input devices, and the sensor data may include one or more user inputs.

The specific routines or methods described herein may represent one or more of any number of processing strategies. As such, various acts illustrated and/or described may be performed in the sequence illustrated and/or described, in other sequences, in parallel, or omitted. Likewise, the order of the above-described processes may be changed.

The subject matter of the present disclosure includes all novel and non-obvious combinations and sub-combinations of the various processes, systems and configurations, and other features, functions, acts, and/or properties disclosed herein, as well as any and all equivalents thereof.

The invention claimed is:

1. A computing device comprising:

a processor configured to:

receive sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electromechanical system is situated;

at a first trained machine learning model configured to receive the sensor data as input, identify a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely;

generate first control instructions based on the first subset of the sensor data;

execute the first control instructions to control one or more actuators of the target electromechanical system;

transmit the second subset of the sensor data to a remote computing device;

in response to transmitting the second subset of the sensor data to the remote computing device, receive second control instructions from the remote computing device; and

execute the second control instructions to control the one or more actuators of the target electromechanical system.

2. The computing device of claim **1**, wherein the processor is configured to:

identify the first subset of the sensor data at least in part by determining that the sensor data included in the first subset is within a first input-space region; and

identify the second subset of the sensor data at least in part by determining that the sensor data included in the second subset is outside the first input-space region.

3. The computing device of claim **2**, wherein, in response to transmitting the second subset of the sensor data to the remote computing device, the processor is further configured to receive a modification to an instruction generation function with which the processor is configured to generate the first control instructions.

4. The computing device of claim **3**, wherein the modification to the instruction generation function includes a definition of the instruction generation function over at least a portion of a second input-space region located outside the first input-space region.

5. The computing device of claim **1**, wherein the processor is further configured to:

at the first trained machine learning model, generate predicted sensor data;

determine a prediction error level for the predicted sensor data relative to the sensor data received from the one or more sensors;

identify, as the first subset, sensor data for which the prediction error level is below a predetermined prediction error threshold; and

identify, as the second subset, sensor data for which the prediction error level is above the predetermined prediction error threshold.

6. The computing device of claim **5**, wherein:

the sensor data has a dimensionality of two or more; and the processor is further configured to:

compute respective prediction error levels for one or more subsets of the plurality of variables; and

for each of the prediction error levels that exceeds a respective predetermined prediction error threshold, identify, as the second subset, respective values of the one or more variables included in the corresponding subset of the plurality of variables.

7. The computing device of claim **1**, wherein the processor is further configured to further train the first trained machine learning model based on the sensor data.

8. The computing device of claim **1**, wherein the processor is configured to generate the first control instructions at least in part at a second trained machine learning model.

9. The computing device of claim **1**, wherein the processor is configured to:

generate the first control instructions based on the first subset of the sensor data in real time as the first subset is received; and

transmit the second subset of the sensor data to the remote computing device for non-real-time processing.

10. The computing device of claim **1**, wherein the processor is configured to identify the first subset of the sensor data and the second subset of the sensor data based at least in part on a communication latency between the processor and the remote computing device.

11. The computing device of claim **1**, wherein:

the processor is configured to receive the sensor data via a local connection selected from the group consisting of a serial connection, a fieldbus, and a local area network; and

the processor is configured to transmit the second subset of the sensor data to the remote computing device via a wide area network (WAN).

12. A method for use with a computing device, the method comprising:

receiving sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electromechanical system is situated;

at a first trained machine learning model configured to receive the sensor data as input, identifying a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely;

generating first control instructions based on the first subset of the sensor data;

executing the first control instructions to control one or more actuators of the target electromechanical system;

transmitting the second subset of the sensor data to a remote computing device;

in response to transmitting the second subset of the sensor data to the remote computing device, receiving second control instructions from the remote computing device; and

executing the second control instructions to control the one or more actuators of the target electromechanical system.

13. The method of claim **12**, wherein:

identifying the first subset of the sensor data includes determining that the sensor data included in the first subset is within a first input-space region; and

identifying the second subset of the sensor data includes determining that the sensor data included in the second subset is outside the first input-space region.

14. The method of claim **12**, further comprising, in response to transmitting the second subset of the sensor data to the remote computing device, receiving a modification to an instruction generation function with which the first control instructions are generated.

15. The method of claim **14**, wherein the modification to the instruction generation function includes a definition of the instruction generation function over at least a portion of a second input-space region located outside the first input-space region.

16. The method of claim **12**, further comprising:

at the first trained machine learning model, generating predicted sensor data;

determining a prediction error level for the predicted sensor data relative to the sensor data received from the one or more sensors;

identifying, as the first subset, sensor data for which the prediction error level is below a predetermined prediction error threshold; and

identifying, as the second subset, sensor data for which the prediction error level is above the predetermined prediction error threshold.

17. The method of claim **12**, wherein the first control instructions are generated at least in part at a second trained machine learning model.

18. The method of claim **12**, wherein:

the first control instructions are generated in real time based on the first subset of the sensor data as the first subset of sensor data is received; and

the second subset of the sensor data are transmitted to the remote computing device for non-real-time processing.

19. The method of claim **12**, further comprising identifying the first subset of the sensor data and the second subset of the sensor data based at least in part on a communication latency between the computing device and the remote computing device.

20. A computing device comprising:

a processor configured to:

receive sensor data from one or more sensors configured to collect the sensor data from a physical environment in which a target electronic device is situated;

at a first trained machine learning model configured to receive the sensor data as input, identify a first subset of the sensor data to be processed locally and a second subset of the sensor data to be processed remotely;

generate first control instructions based on the first subset of the sensor data;

execute the first control instructions to control one or more controllable components of the target electronic device;

transmit the second subset of the sensor data to a remote computing device;

in response to transmitting the second subset of the sensor data to the remote computing device, receive second control instructions from the remote computing device; and

execute the second control instructions to control the one or more controllable components of the target electronic device.

21. The computing device of claim **20**, wherein the one or more sensors are included in one or more user input devices.

22. The computing device of claim **20**, wherein controlling the one or more controllable components includes presenting a graphical user interface (GUI) at a display device.

23. The computing device of claim **20**, wherein controlling the one or more controllable components includes storing data in a non-volatile storage device.

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